Simulation and Flight Test Assessment of Safety Benefits and Certification Aspects of Advanced Flight Control Systems

Dr. James E. Steck, Dr. Kamran Rokhsaz, Mr. Urpo J. Pesonen, Wichita State University, Wichita, KS 67260

Dr. Noel Duerksen, Mr. Sam Bruner, Raytheon Aircraft Company, Wichita, KS 67201

This project is directed to investigating the use of a nonlinear adaptive inverse control method for customized flight control systems as applied specifically to general aviation aircraft. Artificial Neural Networks (ANN) are a key element in adapting to and counteracting the errors due to nonlinearities and noise, and to estimating states in cases of sensor failure. Thus the control system is being designed to adapt to unanticipated partial failure of the flight control system, thus allowing the pilot to continue to safely control the aircraft. The adaptive control system is being develop using Matlab simulink simulations leading to flight tests on a Beech Bonanza F33C Fly-by-Wire Test-Bed that also has a redundant set of mechanical controls. The increased safety and certification issues are examined throughout the development and implementation process.

Advances in modern flight control design provide means to design a simplified control system for general aviation aircraft. This can increase aviation safety and make personal air transport available to a larger group of people who are not aviation enthusiasts ("Highway in the Sky"). SATS (Small Aircraft Transportation System) aims to provide reliable personal air travel for a wider audience, which presents the objective of a flight control system that provides a reduced pilot workload through decoupled control modes and stability augmentation. Such a system also enables pilots with low experience to operate the aircraft in most weather conditions, has an emergency auto-land capability, and adapts to changes in aircraft behavior due to unanticipated actuator/sensor failures or structural damage. McFarland and Calise¹ proposed a method where neural networks and direct adaptive control are used to compensate for unknown nonlinearities while dynamic nonlinear damping provides robustness to unmodeled dynamics. In both studies, a neural network was used to adaptively cancel linearization errors through on-line training. Artificial Neural Networks (ANN) are capable of approximating continuous nonlinear functions with very little memory and computational time required, but due to the empirical character of these methods it has previously been difficult to guarantee sufficient reliability for such a high-risk application as flight control. Using neural networks for nonlinear inverse control of the XV-15 tilt-rotor, Rysdyk et al.² showed theoretically as well as by simulation that the ANN weights remain bounded during on-line training. This is an important step towards certifying aircraft control systems that use Artificial Neural Networks.

Soloway and Haley³ studied reconfigurable aircraft control at NASA, and their model is capable of real-time control law reconfiguration, model adaptation, and identification of failures in model effectiveness. A full six degree-of-freedom (6 DOF) model of a conceptual commercial transport aircraft was used to simulate the elevator freezing in flight, and the algorithm reconfigured itself to use symmetric aileron deflections to control pitch rate, thereby stabilizing the aircraft. Again, an Artificial Neural Network was used to learn the changed dynamics of the aircraft with frozen elevators. Kim and Calise⁴ developed a direct adaptive tracking control using neural networks to represent the nonlinear inverse transformation needed for feedback linearization. It was shown that the adaptation algorithm ensured uniform boundedness of all signals in the loop, and that the weights of the on-line network converged to constant values.

Nonlinear adaptive control designs have been demonstrated for a mid-size transport (NASA) and in X-36 (Air Force) with unanticipated control failures. The NASA demonstration included a piloted simulation using only propulsion for backup flight control. Applicability of an emergency flight control system greatly increases if it

can provide desirable responses over a wide range of unanticipated failures via adaptive control. The following variables have to be taken into account: velocity, altitude, C.G. location, attitude, current configuration, jammed or floating control surfaces, number and location of failed engines.

In the current project, an adaptive nonlinear inverse controller is being designed for a Beech Bonanza F33C single engine general aviation aircraft. The controller will be implemented on the Raytheon Aircraft Company Bonanza F33C Fly-by-Wire Test Bed, which will then be used for test flights. The controller is designed in the Matlab-Simulink. Nonlinear inverse control is used and an Artificial Neural Network is trained on-line to counteract modeling error. An ANN is also used to adapt to changing flying characteristics due to unanticipated failures by taking advantage of redundancy in control.

The nonlinear adaptive control methods of this project are a piece of a much larger effort to eliminate accidents that are related to loss of control, such as, stall, spin, disorientation, over-speeding the airplane, or overstressing the airplane. It is also a goal to bring all non-thunderstorm and non-icing IMC conditions within the capability of all pilots, and to have autoland capabilities that are ILS CAT IIIb equivalent with no pilot training requirement. Types of accidents that can be reduced are controlled flight into terrain and unsuccessful resolution of an emergency due to high pilot workload. Simplified flight controls will allow the pilot to provide full attention to an emergency while the airplane maintains its current path, thus reducing the cognitive effort required to operate the airplane safely. Failures of advanced flight control system, of course might lead to a different type of accident, which must be prevented by proper analysis and certification of the new flight control system. Reliability and safety of such systems specifically require dependable integration of software and hardware

¹ McFarland, M. and Calise, A., "Robust Adaptive Control of Uncertain Nonlinear Systems Using Neural Networks," IEEE Transactions on Automatic Control, July 1997, Short Paper.

² Rysdyk, R., Nardi, F., and Calise, A., "Robust Adaptive Nonlinear Flight Control Applications Using Neural Networks," Proceedings of the American Control Conference, pp. 2595 - 2599.

³ Soloway, D. and Haley, P., "Aircraft Reconfiguration Using Neural Generalized Predictive Control," American Control Conference Proceedings, Vol. 4, pp. 2924 - 2929.

⁴ Kim, B. and Calise, A., "Nonlinear Flight Control Using Neural Networks," Journal of Guidance, Control, and Dynamics, Vol. 20, No. 1, January-February 1997, pp. 26 - 33.